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A GENERIC SIMULATION MODEL FOR SELECTING FLEET SIZE IN SNOW PLOWING OPERATIONS

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ABSTRACT

Accumulated snow on roads poses a threat to traffic systems and rouses significant safety concerns. Snow plowing is often used to recover roads in the event of heavy snow. Due to the unpredictability of weather conditions, it is difficult to determine the overall performance of a certain truck fleet size, thus make it challenging to estimate the number of snow plow trucks needed for a given highway area. The objective of this research is to estimate the truck fleet performance under uncertain weather conditions, and to provide decision support for selecting a reasonable fleet size. A generic simulation model is developed in the *Simphony.NET* environment. Weather, road network, and truck speed data are entered as inputs, and Monte Carlo simulation is used to generate random snow events to quantify the performance. A case study is developed and presented to demonstrate the practicality and feasibility of the proposed model.

1 INTRODUCTION

Winter road maintenance is challenging for many northern countries (Shi 2010). Notably, Canada spends around $1 billion dollars annually in winter road maintenance activities (Andrey et al. 2001). In practice, snow plowing plays a significant role in winter road maintenance to remove as much loose snow on the roads as possible, and to increase mobility and safety (Perrier et al. 2006; Usman et al. 2010). In order to conduct snow plowing activities effectively, efforts have been made to improve planning efficiency. One major aspect of optimizing snow plowing activities is the selection of the truck fleet size and the plowing routes. In previous studies, snow plow routing optimization is considered as a Hierarchical Chinese Postman Problem (HCPP) (Cabral et al. 2004; Ghiani and Improta 2000). The common solution for this problem is to divide the area into several sectors and set one depot at each sector with an assigned truck crew. When the snowstorm comes, trucks will depart from the depot to different road sections and return to the same depot after all roads are cleaned. Due to the complexity of snow plowing operations, however, the challenge is separating a large road network into small sectors and determining the crew size at each depot (Stricker 1970). For example, the size of each sector will affect its crew size. Both the crew size and the combination of roads within this sector must be considered when selecting the plowing route. Additionally, uncertain weather conditions can stall this process because the snow coverage areas by storms are unknown. As such, the roads need to be plowed, and the plowing route varies for each snow event. Considering the random nature of weather events is necessary to resolve these problems. The process of developing simulation models often requires repetitive efforts; a generic model is needed to incorporate the planning process of snow plowing on various road networks. This paper therefore proposes a generic model to simulate snow plowing processes under uncertain weather conditions. This model captures the nature of planning, and can be re-used for various project scenarios with minimal adjustments. Based on the proposed model, the performance of a given fleet size can be evaluated, and a reasonable fleet size can be selected based on a required confidence level.

2 LITERATURE REVIEW

A number of studies have been conducted to ascertain reasonable fleet sizes and route choices for snow removal operations. Most of the existing research uses the operation cost, completion time, and service-time delay as constraints to determine the fleet size. These methods are often seen to be solving a static mathematical problem: e.g. given an objective function of minimizing the travel distance of trucks. For example, Salazar-Aguilar et al. (2012) propose an Adaptive Neighborhood Search approach to minimize the makespan under a given fleet size while considering the synchronized arc routing problem, which requires street segments with more than two lanes to be served simultaneously by multiple synchronized vehicles. Another study conducted by Liu et al. (2014) uses a meta-heuristic method for snow plowing operations based on the capacitated arc routing model. The results suggest that the fleet size, depot location, and routing should be considered together to minimize the total travel time for different trucks while satisfying the service requirements. Siu et al. (2017) have proposed a framework to increase the utilization of truck shops by optimizing shop locations, quantities, and the service area of the shop; this method minimizes the total work effort with considerations of satisfying work duration requirements. These studies, however, assume that the entire service area always snows simultaneously, and do not consider the uncertainty of affected snow areas and the impact on the fleet size.

Assuming uncertain weather conditions results in a more realistically uncertain snow area and demand for the snow plowing trucks. For instance, Chien et al. (2013) have established a fleet-size-estimation model for snow plowing operations under different weather conditions. The fleet size in this model is affected by the weather conditions. Sensitivity analysis was conducted to link the fleet size with a model parameter, such as snow intensity or plowing speed; the result shows that compared with intense snow events, fleet size is more easily to be affected by plowing speed under light snow events. To determine the fleet size from a cost-effective perspective, Abdel-Malek et al. (2014) conducted a cost-analysis to help determine the number of trucks that would minimize the total cost. The proposed contracting model can analyze the tradeoff for fleet sizes under different weather conditions. Another study conducted by Hajibabai and Ouyang (2016) considers the dynamic snow plow fleet assignment under uncertain weather and service disruptions. Based on the data from Lake County, Illinois, the results suggested that the proposed algorithm can more effectively assign the snow plow fleet compared with the rolling-horizon heuristic solution.

Most of the existing research has assumed that for all snow events, all roads will be covered with heavy snow and need to be plowed; which overlooks the random nature of snow events. Some research has considered the stochastic impact area of snowstorms but has aimed at solving the static issues (i.e. mathematical models) related to snow plow trucks, such as minimizing the fleet size, makespan, deadhead distance and the total cost. This study uniquely uses a simulation method to model the performance of different fleet sizes, and uses the confidence level set by the user as a constraint to select a reasonable fleet size. A range estimation of the performance can be generated through multiple iterations, instead of generating one static number. With considerations of both the weather and the route selection, this study focuses on responding to two problems: (1) how to consider the snow plow routes while considering the uncertainty of snow events, and (2) how to determine the truck fleet size for a depot with a certain confidence level.

3 METHODOLOGY

This research proposes a generic model to simulate the snow plowing process (as shown in Figure 1). The model has been developed in the *Simphony.NET* environment, a simulation engine developed at the University of Alberta (AbouRizk et al. 2016a). This model uses the following as inputs: the road network, historical weather data, and the level of service (LOS) class for each road section (usually assigned by the government), along with the maximum plowing time allowed for each LOS class. By changing the input data, the proposed model can be used at different snow removal projects with different road network layouts, weather conditions and LOS requirements. This model consists of three major parts: generating a random snow area, selecting the plowing route, and calculating the plowing time. First, this model will generate a random snow area using historical weather data; next, the plowing work will be assigned to trucks based on a selected truck fleet size; finally, the model will simulate when the plowing work on each road will finish. If the finish time exceeds the maximum allowed plowing time, the work on this road will be considered delayed, and the distance delayed will be calculated. The model generates a probability distribution of the total distance delayed as outputs, which can be used to evaluate the performance of a selected fleet size. Moreover, additional adjustments can be made based on the confidence level required.

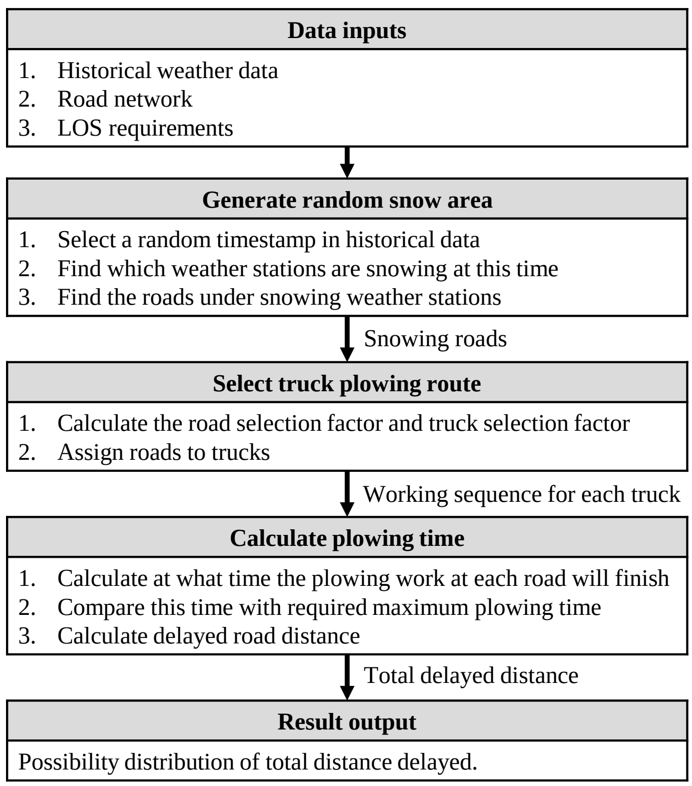

Figure 1: Simulation process.

3.1 Assumptions

The proposed simulation model is developed based on four assumptions:

1. Only plowing operations are considered in this model. Sanding operations or any other activities that require using materials do not apply to this model since the process of truck reloading materials are not calculated (this can be included as future work).
2. Each road is assigned to its closest weather station. If a weather station indicates precipitation, all roads assigned to this weather station are considered as snowing and need to be plowed.
3. All roads are two-way roads. Therefore, trucks are required to return to the starting location after plowing each road.
4. Roads remains passable when covered with snow, and it does not affect the truck speed. Both deadhead travel and plowing speed stays the same under all weather conditions.

3.2 Generate Random Snow Area

Figure 2 shows the flowchart of the "generate random snow area" process. Here, the model uses historical weather data and Monte Carlo simulation to generate a random snow area. All roads within this area will be assigned to trucks for plowing work in the following step. First, the model generates a random number and finds a random timestamp from the database using both this random number and the sequential IDs of the timestamps; next, the model checks the weather status of each weather station at this time. If there is at least one weather station indicating snow at this time, the model will output the roads under snowing weather stations for the next step, otherwise the model will generate a new random number and repeat this process.

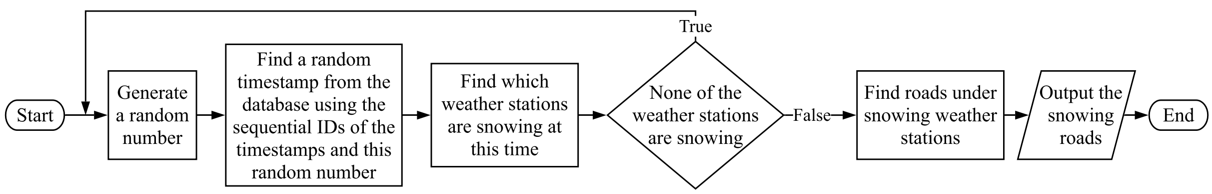

Figure 2: Generate random snow area process.

3.3 Select Plowing Route

After a random snow area is generated, the simulation model assigns the plowing work triggered by weather events to the trucks. Figure 3 shows the flowchart of this process starting with a calculation of the road selection factor for each road. This factor is calculated by satisfying equation (1)

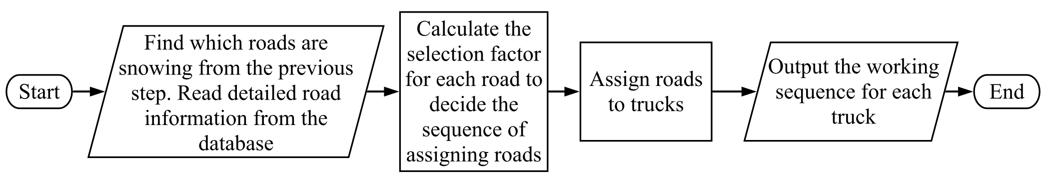

Figure 3: Select plowing route process.

$$F_R = \frac{L_R \times N_L \times 2}{T_{MAX}} \tag{1}$$

where F_R = road selection factor; L_R = road length; N_L = number of lanes; and T_{MAX} = LOS class-stipulated maximum plowing time.

Roads are assigned to trucks starting from the road with highest road selection factor value. Notably, the value of this factor is also the average speed for one truck to plow this road. The higher the value is, the less float time the truck has for the work. Since the truck will conduct plowing work starting from the first road assigned to this truck, this road assignment order makes the best effort possible to avoid work delays. When this value exceeds the average plowing speed, there is a high possibility that one truck cannot finish plowing this road in time, considering additional deadhead travel may be needed before trucks arrive to this road. Therefore, multiple trucks are assigned to this road and share the plowing work. The number of trucks for each road is calculated by equation (2)

$$N_T = \left\lceil \frac{L_R \times N_L \times 2}{T_{MAX} \times V_P} \right\rceil \tag{2}$$

where N_T = number of trucks; L_R = road length; N_L = number of lanes; T_{MAX} = LOS class stipulated maximum plowing time; and V_P = average plowing speed.

When a road is assigned to multiple trucks, all trucks equally share the workload on the same road. When a road is plowed by one truck, the truck always returns to its starting location after plowing. Additional deadhead travel is added to each truck if one road is assigned to multiple trucks. This deadhead equals the total distance of the road subtracting the plowing distance for each truck, which ensures that the trucks can return to the starting location after plowing part of the road. This assignment process also considers a balance of the workload between trucks. The workload for the trucks is calculated using equation (3)

$$W = L_P + \frac{L_D}{2} \tag{3}$$

where W = truck workload; L_P = total plowing distance; and L_D = total deadheading distance.

To make sure all trucks share a similar workload, a truck selection factor is used in the model to decide which road will be assigned to which truck. This factor is calculated using equation (4)

$$F_T = W + \frac{D}{2} \tag{4}$$

where F_T = truck selection factor; W = trucks' current workload (calculated by equation 3); and D = shortest deadhead distance between the road and the current truck location.

When calculating the shortest deadhead distance, the widely-used Dijkstra's algorithm determines the shortest path in the node-network (Dijkstra 1959). The model recalculates the truck selection factor after every time that a road is assigned to one truck. Each road section is assigned to the truck with the smallest truck selection factor value. By using this factor, the priority is given to the truck that a) has the smallest workload and b) is closest to the road section. This approach can balance the workload between trucks and reduce the total deadheading distance. For instance, if the workload value (calculated using equation (3)) of truck A is 15 and the workload value for truck B is 10, and a road is 5 km away from truck A and 10 km away from truck B, then the truck selection factor calculated using equation (4) would be 17.5 for truck A and 15 for truck B. Therefore, this road would be assigned to truck B based on the truck selection factor. This causes more deadhead travel in the work, but it balances the workload between the two trucks. If truck B were 20 km away from the road, however, the truck selection factor for truck B would become 20, and truck A would be selected due to a smaller selection factor value. Thus, trucks will avoid long-distance deadhead travel and can reduce the total workload of the operation. After the road sections are all assigned to trucks, the truck carries out the plowing work following the order of roads assigned. The time taken on each road section is calculated in the next step (section 3.4).

3.4 Calculate Plowing Time

Figure 4 illustrates the process of calculating plowing time. After the plowing route for each truck is selected, the model calculates at what time the plowing work on each road will finish. Here, a probability distribution function of the plowing speed is used to calculate the plowing time. This distribution function is fitted using plowing speed data collected in real construction projects; it has a Laplace distribution with a mean of 42.71 and a scale of 10.60. Figure 5 shows the comparison between the original data and the fitted function. To eliminate extreme situations, a lower boundary at the 5^{th} percentile and an upper boundary at the 95^{th} percentile are added to this function. The plowing time on each road is calculated using a random deviate of this function. Next, the plowing time on each road will be compared with the LOS stipulated time to determine whether or not the operation meets the LOS requirement. If the plowing time exceeds the required time, the model calculates the distance that was plowed on time, and the rest of the road is output as delayed distance. For each snow event generated, multiple simulations of the plowing process under this snow event are executed in this model. Through multiple iterations, the model generates a distribution of the delayed distance under current selected truck fleet size. With this information, further adjustments can be made based on the confidence level required.

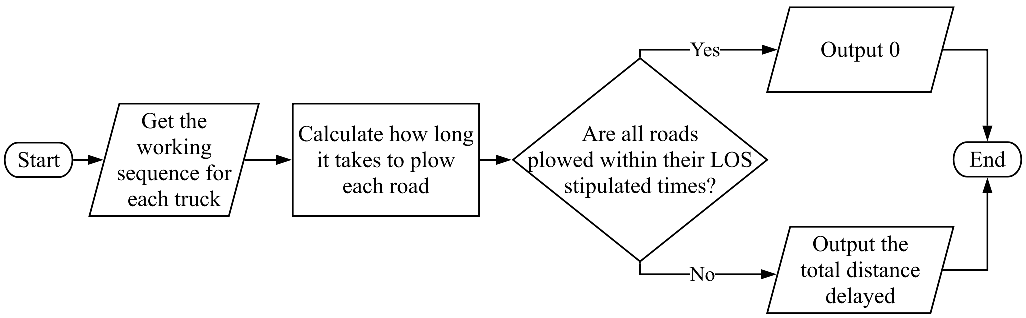

Figure 4: Process to calculate plowing time.

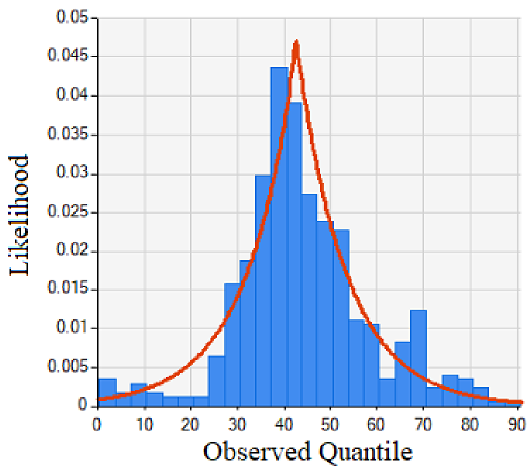

Figure 5: Comparison between original data and fitted distribution function.

4 IMPLEMENTATION

4.1 Database Structure

All input data of this model are prepared and stored in a Microsoft Access database following the structure shown in Table 1. By changing the input data, this model can be reused on different projects. Since most of the original data are stored in separate files and have different formats, data preprocessing is needed in order to: (1) convert original weather data into a uniform format, (2) convert the roadmap into a node-to-node format, and (3) remove redundant weather data to accelerate the simulation program. Notably, this model simulates the overall performance of the truck fleet within the entire period of available weather data, but the performance of a specific season can also be simulated by only using the weather data from that season. Normally, the weather data should have a duration that covers most of the snow season, and include various snow events with different precipitation levels in order to produce reliable results. This database uses a node-to-node format to store the road network information. The road intersections are considered as "nodes," and road sections are considered as connections between two nodes. Each road section should have a consistent LOS class and a continuous number of lanes. If the LOS class or number of lanes changes in the middle of a road section, it should be split into two sections and an additional node should be added at that position. For roads outside the service area, they can be added to the roadmap as "shortcut" roads to let trucks use it for deadhead travelling between nodes. "Shortcut" roads are added to the database without being assigned to a weather station; therefore, these roads will not be assigned to any truck for plowing, since they do not need to be plowed.

Table 1: Structure of the database.

Table Name	**Field Name**	**Description**
GeneralInformation	NumberOfWeatherRecords	Total number of records in the "TimeRange" table
	NumberOfWeatherStations	Total number of weather stations under this shop
	NumberOfRoads	Total number of roads in the map
	NumberOfNodes	Total number of nodes in the map
	StartNode	The node where the shop is located at
	NumberOfTrucks	Total number of trucks in the fleet
Nodes	ID	ID of the node
	ConnectedNodes	ID of the nodes that this node is connected to
LOS	Class	LOS class
	MaxPlowingTime	Maximum plowing time allowed
Road	ID	ID of the road
	LOSClass	Road's LOS class
	LengthKm	Road's length in kilometers
	NumberOfLanes	Number of lanes in each direction
	WeatherStation	The weather station that the road belongs to
	StartNode	ID of the road's one vertex
	EndNode	ID of the road's another vertex
WeatherStation	StationID	Name of the weather stations
TimeRange	ID	ID of the timestamp
	WeatherTime	The timestamp of the weather record
WeatherStationData	StationID	Name of the weather station
	WeatherTime	The timestamp of the weather record

4.2 Simulation Modeling

This model is developed in the *Simphony.NET* environment. Figure 6 illustrates its schematic. Notably, the proposed methodology is not limited to the *Simphony.NET* platform; other simulation software can also be used to achieve the same result. In *Simphony*, virtual entities are created at the beginning of the simulation process. These entities flow through a series of elements that represent different tasks. Calculations are executed when an entity arrives at an element (AbouRizk et al. 2016b). *Simphony* provides multiple modeling elements with different functions by default; the user can use these elements to represent different tasks in the operation by setting unique attributes to each element. Extra codes can also be added to elements if additional calculation is required. In this model, entities that represent snow events are created at the beginning of the simulation process. The processes of generating random snow areas and selecting plowing routes are accomplished in two elements named "Generate Snow Area" and "Select Route" using Visual Basic codes. After the plowing route for each truck is selected, new entities that represent plowing trucks are created. Next, each entity will go through the "Plow" element where the plowing time for each road section will be calculated. The model will then collect the delayed distance, and the possibility distribution of this number will be generated through multiple iterations. *Simphony* also allows users to export the simulation result of each iteration to a Microsoft Excel file. The mean, median, and the confidence interval of the results can be calculated using the exported data.

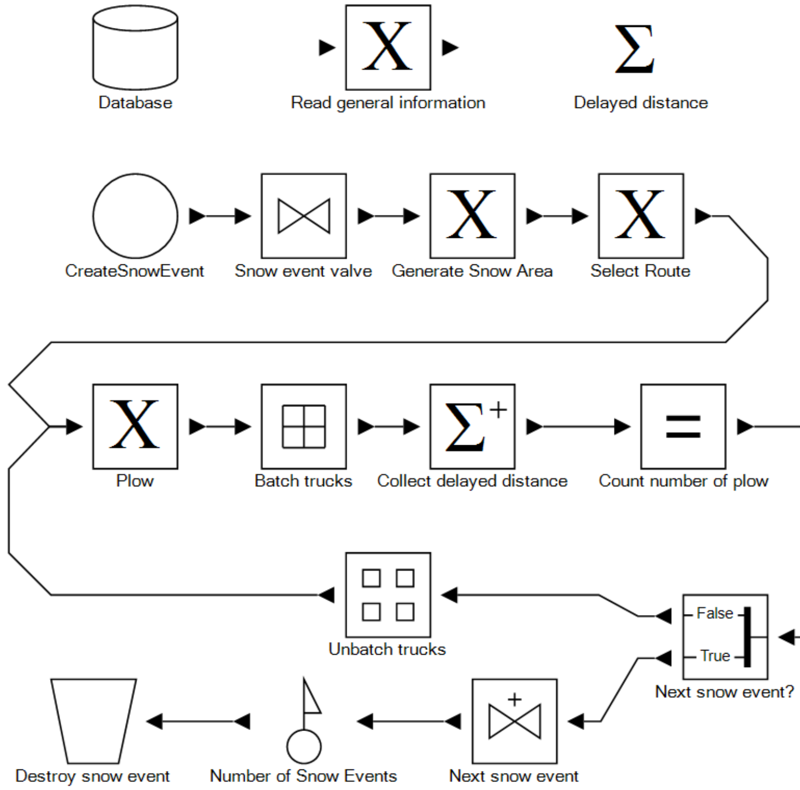

Figure 6: *Simphony.NET* simulation model.

5 ILLUSTRATIVE CASE STUDY

A case study is provided here to demonstrate the functionality and practicality of the proposed model. Figure 7 illustrates the road network, shop location, and weather station locations for this case study.

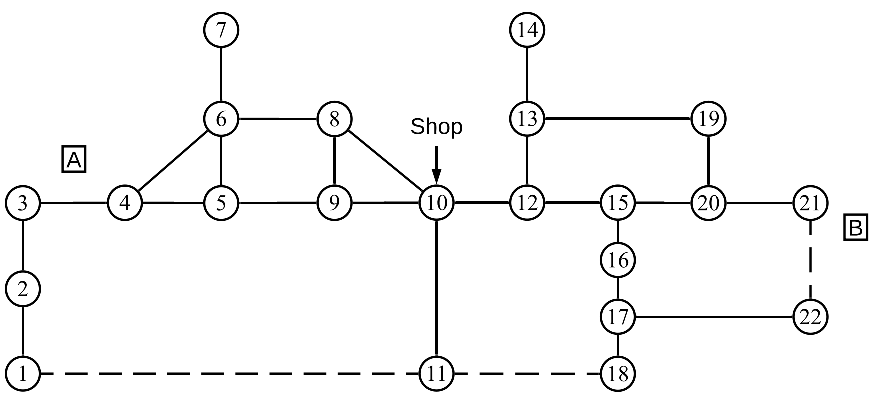

Figure 7: Road network for the example case study.

This road network has 25 roads and 22 nodes; 3 additional shortcut roads are also added to the road network, which are shown as dashed lines in Figure 7. The shop is located at Node 10. Weather data from two weather stations, marked in Figure 7 as A and B, are used to determine the weather situation in this area, and the weather on each road is determined by its closest weather station. The data used here has a 5-minute observation interval within a 108-day period in winter. It has a total of 29501 observations after removing some missing data. Table 2 shows detailed road data. The maximum plowing time allowed for each LOS class is shown in Table 3. The simulation model was run for 5000 iterations. Tables 4 and 5 show the model output result for fleet sizes ranging from 5 to 9 trucks. The average simulation time was about 20 minutes on a computer with 3.2 GHz CPU and 16 GB memory.

Table 2: Road information for the case study.

ID	**LOS Class**	**Length (km)**	**Lanes**	**Weather station**	**Vertex 1**	**Vertex 2**
1	H	14.2	1	A	1	2
2	J	10.54	1	A	2	3
3	C	25.23	2	A	3	4
4	K	3.06	1	A	4	6
5	G	0.75	1	A	5	6
6	G	13.24	1	A	6	7
7	A	3.01	2	A	4	5
8	D	6.82	2	A	5	9
9	B	3.42	2	A	9	10
10	C	1.06	1	A	8	9
11	F	6.22	1	A	6	8
12	H	5.2	1	A	8	10
13	D	23.63	1	A	10	11
14	E	8.75	2	A	10	12
15	I	2.33	1	A	12	13
16	G	13.35	1	A	13	14
17	D	8.77	2	B	12	15
18	I	22.23	1	B	13	19
19	G	11.18	1	B	17	18
20	H	9.98	1	B	16	17
21	F	4.95	1	B	15	16
22	C	10.11	2	B	15	20
23	H	9.7	1	B	19	20
24	F	19.95	1	B	17	22
25	C	5.02	2	B	20	21
Shortcut 1		42.89			1	11
Shortcut 2		12.22			11	18
Shortcut 3		26.3			21	22

Table 3: Maximum plowing time allowed for each LOS class.

LOS Class	A	B	C	D	E	F	G	H	I	J	K
Time (hours)	1.25	1.5	1.75	2	2.25	2.5	2.75	3	3.25	3.5	3.75

Table 4: Possibility of the distance delayed in one operation.

Distance delayed (km)	**5 trucks**	**6 trucks**	**7 trucks**	**8 trucks**	**9 trucks**
0	38.60%	43.75%	51.12%	64.84%	66.41%
< 1	40.05%	45.43%	53.67%	67.26%	68.73%
< 3	42.50%	53.14%	64.15%	72.67%	72.75%
< 5	44.25%	57.14%	67.95%	75.50%	76.59%
< 10	49.32%	66.29%	76.00%	82.35%	83.80%
< 20	63.66%	79.94%	87.72%	89.78%	91.70%
< 30	75.72%	85.80%	91.34%	92.71%	95.35%
< 50	88.20%	90.18%	93.15%	95.58%	98.08%
< 100	93.90%	90.91%	97.74%	99.49%	99.90%
< 200	94.24%	95.19%	99.98%	100.00%	100.00%
≥ 200	5.76%	4.81%	0.02%	0.00%	0.00%

Table 5: Maximum distance delayed in one operation.

Number of trucks	5	6	7	8	9
Maximum distance delayed (km)	365.0	307.7	211.2	157.0	113.9

The simulation shows the delay possibilities (for different fleet sizes) of one snow removal operation to clean up all snow-covered roads after one snow event. It provides valuable information for selecting a reasonable fleet size with different confidence level requirements. Since the simulation model provides a range estimation of the performance, criteria can be set at any level to find the minimal fleet size required. For example, if having a 60% confidence level is required that no road will be delayed in the operation, a minimal fleet size of 8 trucks will be needed based on the simulation result. Similarly, if a 70% confidence level is required for having fewer than 10 kilometers delayed in a single operation, the minimal fleet size needed will be 7 trucks. Criteria like “maximum distance delayed” in a worst-case scenario, or “maximum possibility allowed” to limit distances delayed can also be used to select a reasonable fleet size.

6 VALIDATION TECHNIQUES

This model is validated using real-world data obtained from a shop with 4 trucks during its operations in November and December 2018. For each truck at this shop, an average delayed road distance in one trip is calculated using data from 5 trips of the truck. The total delayed distance is determined by the sum of the 4 trucks. The simulation model was run for 5000 iterations, the real operation data is on the 49^{th} percentile of the simulation result; it has a 1.19% difference with the median value and a 16.53% difference with the mean value. Considering the time waiting for traffic lights, time spent making turns, and other factors affecting the trucks’ productivity are not calculated in this model, this result is considered to be acceptable.

7 CONCLUSION

This study is aimed at selecting a reasonable fleet size under uncertain weather conditions. By evaluating the performance of a given fleet size, a reasonable fleet size can be selected based on a required confidence level. The simulation approach includes: using the Monte Carlo method to sample random snow areas based on historical data, selecting the plowing route for trucks, and calculating the time-cost of plowing operations based on real-world speed data. The feasibility of proposed model was demonstrated through an illustrative case study. The performance of different truck fleet sizes is simulated, and the results show the potential risk of failure for different fleet sizes. This model provides a new decision support tool for developing policies and strategies for the assignment of different numbers of trucks to a depot. The proposed model can also incorporate advanced weather information from a forecast system, which provides detailed weather information for every road section. Future work may include adding a feature to the model to automatically select the minimal fleet size for a given confidence level, incorporating the effects of truck breakdowns, and generalizing the model for other fleet types, such as sand trucks, to include loading and unloading materials. The authors recommend that future studies be conducted focusing on these issues.

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REFERENCES

Abdel-Malek, L. L., S. I. Chien, J. N. Meegoda, and H. Yu. 2014. "Approach to Fleet Contracting for Snow Plowing Operations". *Journal of Infrastructure Systems* 20(2):04014006.

AbouRizk, S., S. Hague, R. Ekyalimpa, and S. Newstead. 2016a. "Simphony: A Next Generation Simulation Modelling Environment for the Construction Domain". *Journal of Simulation* 10(3):207-215.

AbouRizk, S., S. Hague, and R. Ekyalimpa. 2016b. *Construction Simulation: An Introduction Using Simphony*. 1st ed. Edmonton, Canada: University of Alberta.

Andrey, J., B. Mills, and J. Vandermolen. 2001. "Weather Information and Road Safety". Institute for Catastrophic Loss Reduction, Toronto, Ontario, Canada. https://www.iclr.org/wp-content/uploads/PDFS/weather_information_and_road_safety.pdf, accessed 5th August 2019.

Cabral, E. A., M. Gendreau, G. Ghiani, and G. Laporte. 2004. "Solving the Hierarchical Chinese Postman Problem as a Rural Postman Problem". *European Journal of Operational Research* 155(1):44-50.

Chien, S. I., S. Gao and J. N. Meegoda. 2013. "Fleet Size Estimation for Snowplowing Operation Considering Road Geometry, Weather, and Traffic Speed". *Journal of Transportation Engineering* 139(9):903-912.

Dijkstra, E. W. 1959. "A Note on Two Problems in Connexion with Graphs". *Numerische Mathematik* 1(1):269-271.

Ghiani, G. and G. Improta. 2000. "An Algorithm for the Hierarchical Chinese Postman Problem". *Operations Research Letters* 26(1):27-32.

Hajibabai, L. and Y. Ouyang. 2016. "Dynamic Snow Plow Fleet Management Under Uncertain Demand and Service Disruption". *IEEE Transactions on Intelligent Transportation Systems* 17(9):2574-2582.

Liu, G., Y. Ge, T. Z. Qiu, and H. R. Soleymani. 2014. "Optimization of Snow Plowing Cost and Time in an Urban Environment: A Case Study for the City of Edmonton". *Canadian Journal of Civil Engineering* 41(7):667-675.

Perrier, N., A. Langevin, and J. F. Campbell. 2006. "A Survey of Models and Algorithms for Winter Road Maintenance. Part I: System Design for Spreading and Plowing". *Computers & Operations Research* 33(1):209-238.

Salazar-Aguilar, M. A., A. Langevin, and G. Laporte. 2012. "Synchronized Arc Routing for Snow Plowing Operations". *Computers & Operations Research* 39(7):1432-1440.

Shi, X. 2010. "Winter Road Maintenance: Best Practices, Emerging Challenges, and Research Needs". *Journal of Public Works & Infrastructure* 2(4):318-326.

Siu, M. F. F., C. Liu, R. Wales, and S. AbouRizk. 2017. "Operation Effort Optimization for Planning Performance-Based Snow-Removal Projects". *Journal of Computing in Civil Engineering* 31(6):04017060.

Stricker, R. 1970. "Public Sector Vehicle Routing: The Chinese Postman Problem". MSc dissertation, Massachusetts Institute of Technology. https://dspace.mit.edu/bitstream/handle/1721.1/27901/06261040-MIT.pdf?sequence=2, accessed 5th August 2019.

Usman, T., L. Fu, and L. F. Miranda-Moreno. 2010. "Quantifying Safety Benefit of Winter Road Maintenance: Accident Frequency Modeling". *Accident Analysis & Prevention* 42(6):1878-1887.

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